Design Variation through Richness of Rules Embedded in LEGO Bricks

The ever-increasing body of engineering standards, regulation and patents have potential to over-constrain the design space, and correspondingly impact innovation in new products. In order to explore this phenomenon, the link between richness of embedded design rules and the resulting design variation in a simple LEGO spaceship was explored. The method, LEGO bricks assigned rules and tagged with RFID tags, allowed the participants to playfully explore spaceship design with four levels of rule richness. Brick adjacency matrices were generated and the matrix entropies calculated. Analysis of the variance of the entropy distributions showed that the rules had a significant effect on the design variation but this was only significant between levels 1 (no design information) and 4 (richest design rules). This suggests that a point exists at which the richness of design rules limit design variation. Improvements to the experiment were posited as further work. The next step is to investigate this point and explore the trade-off between design rules and innovation.

1 INTRODUCTION

In this paper an experiment is described in which the effect of embedding design rules electronically inside LEGO bricks is explored, in order to explore the impact of design rules on design freedom and ultimately to investigate approaches to manage and evolve design rules.

Design rules exist in many forms in the design process, and include things such as engineering, safety, environmental standards. When considering design rules they possess two important characteristics, namely the expression of the rules and how they are delivered. Delivering design rules effectively can be challenging due to issues around information overload from the high quantity of rules. Design rule expression is important because the explicitness of the rules may potentially impact innovation and creativity by over-constraining the design space. The authors are interested in the expression of design rules and how varying their ambiguity can address concerns around reduced levels of innovativeness.

The experiment reported in this paper forms part of a larger project called PhysiCAD (Boa, et al., 2016). PhysiCAD is a technical feasibility study into creating tangible interfaces for computer aided design using construction kits, such as LEGO. The motivation for PhysiCAD is two-fold: to improve access to digital design tools for non-skilled users; and to add physicality back into digital design so that experienced designers can intuitively explore their design space. CAD is considered to be more than just solid modellers and also includes systems that help manage any aspect of the design process such as constraint management, costing and DFM (Design For Manufacture).

The experiment in this paper utilises the InstructiBlocks system (Bennett et al., 2017) which is part of the PhysiCAD project. InstructiBlocks is an electronic LEGO system in which individual LEGO bricks have embedded RFID tags within them. The InstructiBlocks system can be seen in Figure 1. Users can scan LEGO bricks on an RFID reader and, on separate computer screen, design rules, or any other information about the brick being scanned, is shown. We utilise the InstructiBlocks system to embed design rules in individual LEGO bricks that when followed by a user result in the construction of a simple LEGO model. An advantage of the InstructiBlocks system is the quick and playful exploration of design rules, constraints or information.

InstructiBlocks also affords a potential solution for dealing with the complexity of design rules by distributing them amongst individual elements. However, this aspect of the system is not considered in this paper and is not discussed further.

The following sections cover the method chosen for the experiment, the data recorded and discussion around the approach and results.

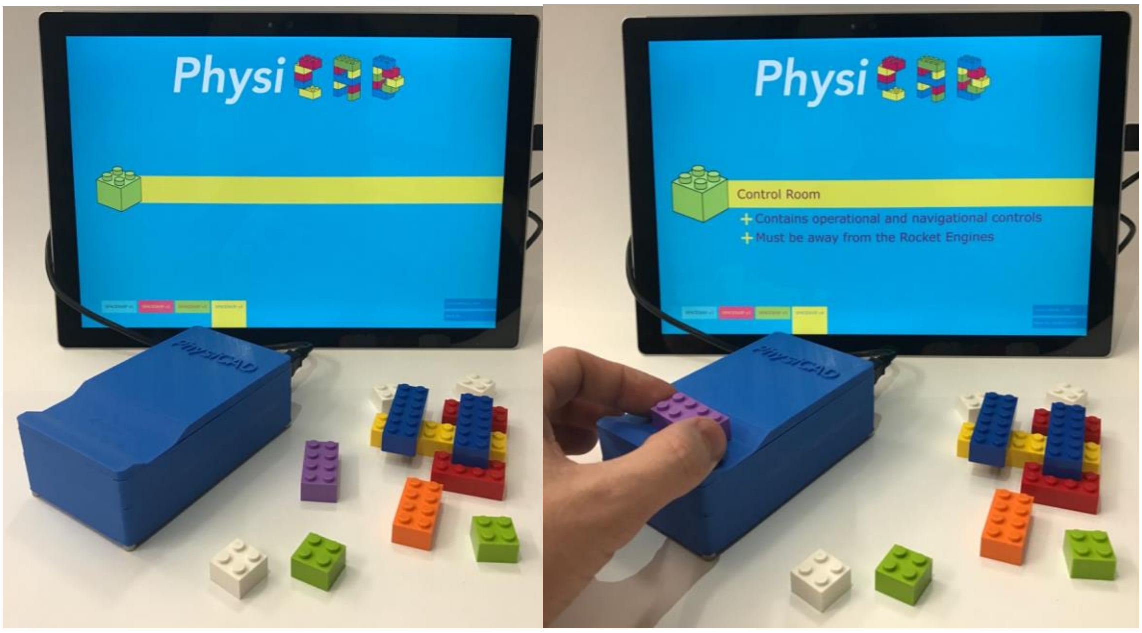


Figure 1: Two images showing the InstructiBlocks system and a user scanning a brick

2 BACKGROUND

Between 1994 and 2015, the ISO 9001 Quality Management Standards - one of the most widely used quality standards - grew nearly four-fold in length (British Standards Institution, 1994), (British Standards Institution, 2015). Similarly, the number of patent applications filed to the European Patent Office grew by 32% between 2006 and 2015 (European Patent Office, 2015)

This ever-increasing body of engineering standards, regulation and patents has the potential to lead to over constraining of the design space and a corresponding impact on innovation in new products (Blind, 2013), (Blind, 2012). Standards are important to ensure that products meet quality, safety and environmental requirements and, according to Blind (2012) and Blind (2013), when managed correctly can lead to innovation. Standards can be considered as a design rule simply because they have to be adhered to and they affect the development of the product.

Given this massive growth in design rules their management and innovative interpretation is increasingly challenging. The quantity and interconnectedness of these rules also makes detecting violations of the rules difficult, leading to issues in design rule compliance checking and verification.

There are several aspects to design rule management which make it challenging. InstructiBlocks as a system has the potential to address two of these challenges: how the rules are delivered and how the rules are expressed. Design rule delivery is challenging because there are so many of them which can result in issues of information overload. Design rule expression is important because the explicitness of the rules may potentially impact on interpretation, and hence innovation and creativity, by over constraining the design space. This paper looks at one aspect of design rule management with regards to the InstructiBlocks system – the richness of the rules.

When expressing rules, there is a balance between ambiguity and explicitness, as well as quantity. Bennett et al. (2017) investigated rule ambiguity when building a model, and showed that rule ambiguity increased design variation and playful interpretation of rules when building simple LEGO models. By increasing the ambiguity of design rules, fixation on rigidly meeting the rule was reduced and the corresponding variation of the LEGO models increased. The study reported in this paper builds on Bennett et al.'s work by exploring how the richness of the embedded rules affects design variation of simple LEGO models.

The richness of design rules is highly contextual and dependent on the product being designed. Design rules can be considered to increase richness as information about the rules interaction with other rules, the product, and its environment also increase. For example, a simple design rule might concern only a single component. Relating the design rule to the component's function within the product would increase the rule's richness. The level of richness can further be increased by relating the component to others. The richness of the rule set is therefore independent of the order in which they are expressed. It is the accumulation of these expressed which give rise to the richness of a component's rules.

In context of the experiment reported in this paper, the authors define richness as the number of rules associated with each LEGO element. Table 1 shows the different levels of rule richness and a description of them. To increase the richness of the rules, the three categories (after the 'System' category) were added consecutively and cumulatively to the LEGO bricks in each subsequent scenario. This reduced the ambiguity of the rules, making the design requirements more explicit.

Table 1. A table showing the level of rule richness and their description

Rule number	Rule richness level	Rule type	Rule description
1	1	System	Geometric size of brick and quantity in system. No information relative the model being constructed.
2	2	Descriptive	A short description of the component relative to the model being constructed
3	2+3	Functional	An explanation of the component (brick's) function relative to the model being constructed
4	2+3+4	Location	A description of the component's location relative to other components in the model being constructed

The problem the authors are considering is the re-structuring of standards and regulations, along with their expression, to improve design innovation. The results from this study will build an understanding of how the expression of design rules affects design innovation and variation.

3 METHOD

The experimental approach involved asking participants to build a spaceship in four scenarios where the embedded rules increased in richness.

3.1 LEGO Model to be constructed

A spaceship was chosen as the simple LEGO model to be built by the participants. There are no strong conventions in the layout of space ships, ensuring the possibility of a large variation of models. Due to fixation effects (Ward, 1994), little variation would be expected should a system familiar to participants be selected, such as a car. It is also easy to imagine functional requirements, but the lack of established convention leaves the combination and meaning of these rules open to interpretation. Furthermore, a simple model was needed so that the participants only needed a few minutes to construct it, a spaceship can be approximated with a limited number of bricks ensuring a fast build time. Finally, the spaceship has been successfully used in previous work (Bennett, et al., 2017) and so was considered a suitable option.

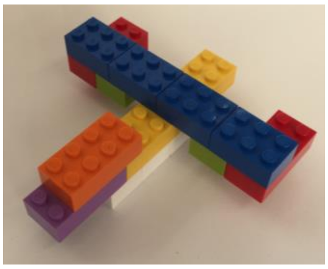


Figure 2. An example of the simple spaceship model

3.2 InstuctiBlocks Rig

The InstructiBlock rig hardware consisted of a 125kHz RFID reader (ID-12LA) connected to an Arduino Mega handling serial data pass through to the host PC. The RFID tags used were 16-byte passive 125kHz glass capsules which were embedded inside the LEGO bricks. Figure 3a shows the hardware setup including the 3D printed enclosure for the Arduino Mega and the RFID reader. 14 LEGO bricks were embedded with rules, the sizes and quantities can be seen in the first column of Table 2. Seven classes of bricks were used, where bricks of the same colour were considered to be in the same class.

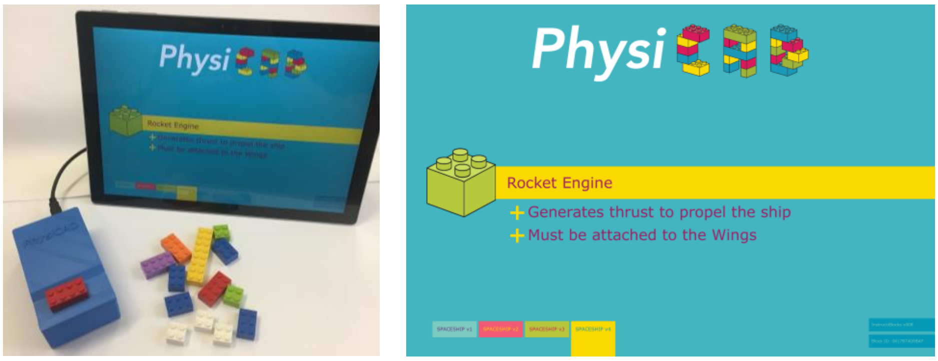


Figure 3a & b. A picture showing the enclosed RFID reader and Arduino Mega and the LEGO bricks. A screenshot of the user interface showing the rules of the bricks.

There were two elements to the software side of the rig: the Arduino code and the user interface. The Arduino code consisted of a serial pass through function that reported the tag information to the PC. Processing (Processing Foundation, 2016) was used to produce a graphical user interface to show the rules for each brick when it was scanned. This script parsed the tag information and compared it to a list of known tags, if correct the rules were then displayed. It also recorded the interrogation sequence for the model built and saved it for analysis. Figure 3b shows a screenshot of the user interface. The rules are shown in the middle, and the rule richness can be selected at the bottom.

3.3 Task and Participants

The design task was to build a spaceship using all 14 of the LEGO bricks whilst adhering to the design rules embedded in the parts. The task was repeated four times with differing levels of rule richness.

3.3.1 Scenarios and Rules

In each scenario, the richness of the rules was increased so that builds were going from least to most constrained. The presentation order was fixed for all participants. Table 2 shows the rules for the four scenarios. In the first scenario, there were no rules however the size and quantity of each class of brick was shown to keep the scanning element consistent between the scenarios. This also allowed the participants to familiarise themselves with the system. Rule level 3 showed the bricks' functions as well as their description, and 4 showed relative location, function and description. This increasing level of specification in effect reduces design freedom of consecutive designs, with high specification mimicking design scenarios operating under high levels of standards.

Table 2. The four scenarios showing the rules for each of the brick classes

Brick Colour	**Rule Level 1: System**	**Rule Level 2: Description**	**Rule Level 3: Function**	**Rule Level 4: Relative Location**
			Plus level 2	**Plus level 2 and 3**
Red	Size: 2x4, Quantity: 2	Rocket Engine	Generates thrust to propel the ship	Must be attached to the Wings
Yellow	Size: 2x8, Quantity: 1	Fuselage	Core of the ship providing access between modules	Must connect Living Quarters and Control Room
Green	Size: 2x2, Quantity: 2	Fuel Tank	Contains fuel for the rocket engines	Must have an adjacent face with a Rocket Engine
Blue	Size: 2x3, Quantity: 4	Wing	Generates lift in atmosphere	Must be directly attached to the Fuselage
White	Size: 2x2, Quantity: 3	Living Quarters	Houses the crew and passengers	Must be adjacent to another Living Quarter
Purple	Size: 2x4, Quantity: 1	Control Room	Contains operational and navigational controls	Must be away from the Rocket Engines
Orange	Size: 2x4, Quantity: 1	Comms Module	Allows communication with home planet	Must be attached to the top of the Control Room

3.3.2 Participants

20 participants took part in the experiment. They had a mean age of 27.6 with a standard deviation of 5.96. Of the 20, 19 were male and the majority had a background in mechanical engineering at degree level or higher.

3.4 Data Capture

Three methods of data capture were performed during the experiment: photos of the models, interrogation sequence captured through data logging and a questionnaire. Photos were taken of each of the four models the participants built, which were then clustered by a panel of experts into similar groups. The panel of judges were asked questions about their grouping rationale. The goal of clustering is to identify the level of similarity within the outputs and hence potential restriction from the rule set. In addition, to this an algorithmic approach was used to measure to the design variation.
The participants scan bricks on the RFID reader to interrogate the rules associated with that brick, with the order in which they scan the bricks forming the interrogation sequence. This was recorded for each of the four rule levels as the participants built their models. Finally participants completed a questionnaire about their brick association in the first scenario and then some overall questions about the InstructiBlock system.

4 RESULTS

In this section the results from the experiment are presented regarding the observed design variation across the participants' models.

4.1 Clustering

Structural topology, in the context of this paper, is the overall shape and structure of the models that the participants built. Clustering based on structural topology was performed by a panel of experts comprising of senior engineers, and occurred for each of the four rule richness levels. The primary considerations that the panel cited for their clustering rationale was the colour locations and characteristics of the overall form including aspect ratio and relative proportions.
Table 3 shows the number of clusters as well as the maximum, minimum and average populations. The significance of the number of clusters is that more clusters show more variation between the models. As the level of rule richness increased the number of clusters decreased, indicating that design variation reduced. However, only Level 4 showed reasonable clustering - with the other levels mostly clustered as individuals or pairs as shown by the average size in Table 3.

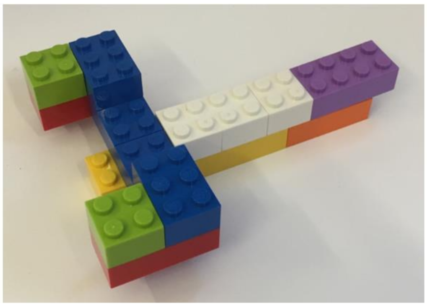
Table 3. Showing the number of clusters and their sizes for the four rule richness levels.

	Rule Level 1	**Rule Level 2**	**Rule Level 3**	**Rule Level 4**
Clusters	14	11	11	5
Max Cluster Size	3	4	3	7
Min Cluster Size	1	1	1	2
Av. Cluster Size	1.43	1.82	1.82	4.00

The large number of clusters in the Levels 1-3 suggest that using the structural topology does not reveal much and it is hard to test with a robust clustering rationale. An alternative approach of looking at the data was used, brick adjacency entropy.

4.2 Entropy of Adjacency Matrices

From the photos of the participants' models, adjacency matrices were constructed. These consisted of counting the number of joins each brick had with another brick, grouped by class. Bricks were considered adjacent if any of its six faces were coterminous with another brick. From these matrices it was possible to calculate the relative entropy for that model. Entropy here is a measure of a class of brick's connectedness to other brick classes in the model. Low entropy indicates that the brick class is isolated and has few connections to other classes. Entropy values are contextual, but the variance in them can be considered as an indicator for design variation. That is the greater the variation the greater the distribution of entropy values for a given rule level.



4	White	Green	Blue	Purple	Orange	Red	Yellow
White	2	0	2	1	1	0	3
Green	0	0	2	0	0	2	0
Blue	2	2	3	0	0	4	2
Purple	1	0	0	0	1	0	0
Orange	1	0	0	1	0	0	1
Red	0	2	4	0	0	0	0
Yellow	3	0	2	0	1	0	0

Figure 4. An example of a spaceship with its adjacency matrix

Figure 4 shows a built spaceship model with its corresponding adjacency matrix. The matrices were calculated for each of the participants over all of the scenarios.

4.2.1 Calculating Entropy

The Shannon Entropy Formula (Shannon, 1948) was used to calculate the entropy for each of the adjacency matrices.

$$H(X) = -\sum_{i=1}^{n} P(x_i) \log_2 P(x_i) \qquad (1)$$

In order to calculate the entropies, the matrices had to be normalised so that the sum of all their elements equalled one. They then could be entered into Equation 1, returning the entropy for that matrix. Entropy calculations were performed using MATLAB.

4.2.2 Analysing Spaceship Model Entropy

From the entropy values for the four scenarios, a kernel density estimation was applied to estimate the probability density functions. These were plotted to graphically inspect the effect of the rules on entropy and to check the suitability of the data for further analysis. The plots can be seen in Figure 5.

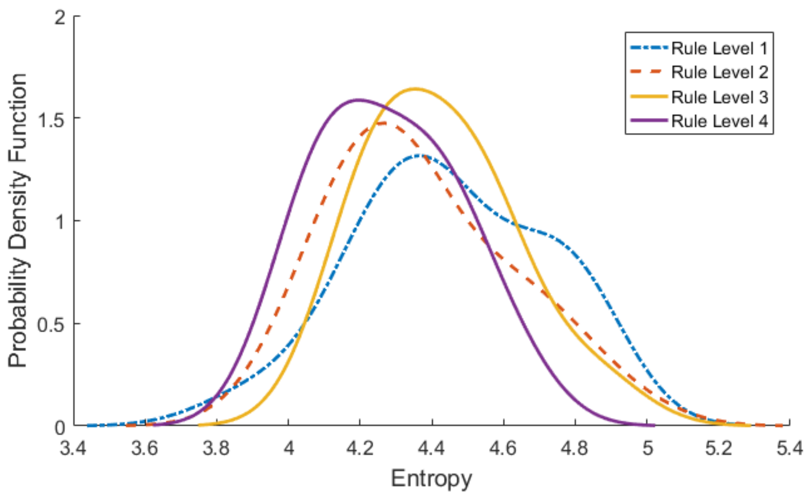


Figure 5. Probability density functions of entropy for the four scenarios

As can be seen in Figure 5, Rule Level 1 has the largest spread showing that it had the greatest variation between designs. Conversely, Level 4 has the lowest spread giving the least variation in the design space. Levels 2 and 3 sit in the middle.

Two way analysis of variance (ANOVA) was performed on the entropy data. This allowed the effect of the participants and rule levels to be tested against a null hypothesis of having no effect. Table 4 shows the results of the hypothesis testing. It shows that while the individual participants have the greatest effect on the outcome of the design variation, the rule level also has a significant effect.

Further statistical analysis was performed using the ANOVA results. This consisted of testing the difference of means between scenarios. This found that only Rule Levels 1 and 4 were significantly different at a 95% confidence interval. Figure 6 shows the means plotted, along with their error bars.

Table 4. Source of data variability, their P-Value and significance

Variability Source	P-Value	Significance P<0.05	Significance P<0.01
Rule Level	0.0339	Yes	No
Participant	0.0069	Yes	Yes

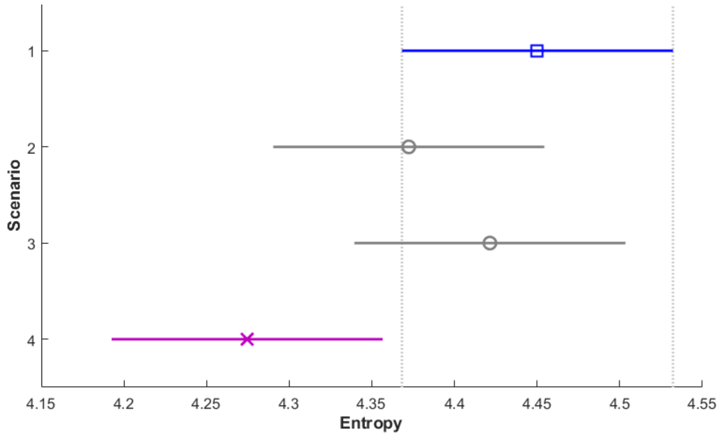


Figure 6. Analysis of difference of means, showing that the scenarios with rule levels 1 and 4 are significantly different

4.3 Interrogation Sequence Data

The interrogation sequence was captured as the participants scanned each brick. Due to the repeated nature of some of the component classes, some participants learnt that they did not need to scan every brick but rather only every class. According to the questionnaire data, most of the participants found the rules easy to remember which likely resulted in fewer repeat scans of bricks. This, combined with the class type learning, meant that the sequence data was not deemed useful for the purpose of measuring how participants explored rules of built models.

5 DISCUSSION

This section discusses the results and comments on the chosen method and its suitability for studying design rules and their impact on design variation.

5.1 Results

The study results are discussed with considerations on how they can be improved and their impact.

5.1.1 Clustering

Clustering should have provided a clear and intuitive insight into how the design rules affected the variation of the built models. However, there were a couple of issues that meant it was not the ideal way to represent the results in this study: the clustering method and the number of participants.

The clustering rationale was chosen before the models were viewed. The choice of structural topology initially seemed reasonable as it would be time efficient looking at the overall shape of the models, however it was difficult to quantify 'shape' in practice. This resulted in a clustering approach that is hard to replicate with another group of experts performing the clustering. A better approach would be to use a more precise method for determining the models' shape. One way would be to count individual stud distances and map them, however this would be incredibly time consuming unless there was a way to scan the models. This would allow a more direct comparison of the spaceship models and a more reproducible way to cluster them.

Due to the small number of participants, 20, clustering the models in each of the four rule levels was difficult due to the lack of common features between models. The results show that, excluding rule level 4, the three rule levels had an average cluster size less than 2. This meant that the clusters only contain one or two models. If the study was performed with a much larger group, over 100 participants, then it is expected that the clustering would be more robust.

The advantage of clustering is that similar models can be grouped together showing the different structures while measuring design variation, an affordance the entropy data does not allow. It is also a more intuitive way to view and understand the data and is easier to use when the number of models increases or they have more components.

5.1.2 Entropy

The entropy of adjacency matrices was used as an alternate approach for measuring the design variation. The adjacency matrices were generated by hand, which was slow in this study and would be prohibitive with a larger number of participants and model bricks. Despite this, the entropy of these matrices allowed the authors to analyse the data more reliably.

The absolute entropy value provides a measure of the inter-connectedness of the brick classes in each model, but by itself it does not shed any light on design variation in each of the scenarios. The more powerful measure is the variance of the distribution of entropies. The distribution was estimated using the kernel density function, with a sample of 20 data points. A smaller spread (lower variance) shows that the spaceship models have similar entropies, therefore similar assemblies, resulting in a less varied range of models. By using the variance of the entropies distributions, a more repeatable approach is achieved. The results show that the design variation is reduced as the richness of the rules is increased. Further analysis using ANOVA, found that while the participants have the largest effect on the outcome of the designs, the rule richness level also has a significant effect. This was statistically proven between levels 1 and 4, but was inconclusive between levels 2 and 3 and the other levels. This showed that while the rules increased in richness, the levels of richness (see Table 1) were too close together - with the two furthest apart showing a statistically significant difference.

Using the entropy, in this manner allows for different models to be robustly compared and the design variation to be calculated, however, as the matrices are generated from brick adjacencies, the overall form of the spaceships is lost. This can result in models with similar entropies having different structural topology.

5.1.3 Secondary Data

Due to learning biases and relatively short rules, participants did not have to scan bricks every time as the information was either repeated or remembered. On top of this, as the bricks could be assembled in the model without scanning them a discontinuity appeared between the interrogation sequence and build sequence. As a result, the interrogation sequence data did not show anything conclusive about the participants' design behaviour. The interrogation sequence would be a much more powerful tool at a larger scale were there are many more components to use and the rules are lengthier or more complicated. It would allow for greater insight into how users approached a complex design task with embedded rules by more accurately recording their interaction with models.

5.2 Chosen Method

The first thing to say about the method was the choice of a simple model. This allowed the participants to build all four models in around 10 minutes. The short nature of the experiment lent its self to participant engagement and enthusiasm.

As was shown in the results, there was no significant difference between rule levels 2 and 3. The authors believe that this stems from the fact that the majority of the participants were engineers. Meaning that adding the functional rule ("Rocket Engines produce thrust to propel the ship") to the descriptive rule ("Rocket Engines") did not provide additional richness for the participants as all it was doing was making their implicit knowledge explicit. This increase in richness would have been more important to non-experts as it might have added useful contextual information to the components.

The component classes were kept consistent throughout, with the richness increasing in subsequent models. This increase in richness was undertaken to ensure that the participants were not learning 'richer' rules and applying them to the less rich models later. Keeping the component classes the same allowed models to be compared across rule sets. However, this meant that there was some learning bias as the participants used their experience of brick classes from previous models to inform their later ones. It would be worth considering modifying the approach to change the brick classes so that, while the participants were still building a spaceship, they had different classes associated with the physical bricks from the previous build task. This would remove some of the learning bias observed between rule levels.

Furthermore, the participants came from a predominantly engineering background and this would have certainly affected how they viewed the problem of designing a spaceship. It would be useful to repeat the experiment with participants from a wider range of backgrounds, both technical and non-technical. Overall, the method is an effective approach to studying design rule impact on output variation

5.3 Further Work

There are several aspects of the experiment that could be improved in further work. The first is to swap the RFID reader box for a wand that could be used to interrogate bricks in situ. Participants found that it was impossible to verify their model was compliant with the rules without taking it apart to rescan bricks. The addition of the wand would allow for quick and easy rule verification.

A method for digitising the participants' models should be explored so that larger and more complex models can be analysed for clustering or similarities using computers - rather than by hand.

Finally, the richness levels and their rules chosen should be refined in future work, this scoping study found that the proposed levels of richness were too similar (Levels 2 and 3) to incite significant changes in design output. Including rules that constrain the models further would be useful, even up to an 'instruction set' that explicitly shows the one way to make a model.

6 CONCLUSION

This study explored a link between richness of embedded design rules and the resulting design variation in a simple LEGO spaceship. The method of placing RFID tags in LEGO bricks and assigning them rules, allowed the participants to playfully explore spaceship design with varying rules. Four rule richness levels were tested: 1. no design information, 2. a description, 3. description and function, and 4. description, function and location with each participant building a spaceship in each of the scenarios. From the photos of the models, clustering was performed. However, this proved to be a challenging approach for measuring the design variation. Instead, brick class adjacency matrices were generated and the matrix entropies calculated. The variance of the entropy distributions was used as a method of determining the design variation. It was found that the rules had a significant effect on the design variation but this was only significant between levels 1 and 4. Improvements to the experiment were posited as further work.

Based on feedback from the participants and the authors' observations, InstructiBlocks' has been envisaged in many different scenarios. These include educational puzzle toys to collaborative space layout configuration to electronic circuit design - all associated with tangibility and quickly being able to explore rules and constraints.

From this study, the results show that there is a point at which the richness of design rules limit design variation. The next step is to investigate this point and explore the trade-off between design rules and innovation; where the rules cover safety, quality and environmental as constraints but their expression and delivery can improve innovation.

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